

Twelfth International Multi-Conference on Information Processing-2016 (IMCIP-2016)

## Enhancement in Time for Feature Extraction & Blending for Panoramic View Generation

Shubhankit Saxena\*

*National Institute of Technology Agartala, Agartala 799 046, India*

---

### Abstract

This Paper concerns with the comparison of time taken to extract the image features. Several previous approaches have been used for panoramic image stitching on different qualities of images which affects the time taken for extracting and matching the features of various images which are stitched together to generate the panorama.

© 2016 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Peer-review under responsibility of organizing committee of the Organizing Committee of IMCIP-2016

**Keywords:** Homography; Image Stitching; Panorama; RANSAC; SURF.

---

### 1. Introduction

In today's digital world there has been an exponential growth in panoramic image generation. Panorama is a Greek word which means "all sight". Panorama is a broad view representation of any space. Panoramic image generation is being widely used in paintings, photography, seismic images and also in film industries. For example, many tourist websites provides local street views & Bing maps provides a visualization as if the user is present in a moving vehicle. For desired panoramic generation many orderly snapshots covering the whole area is required. Like all other processes panoramic image generation is also having some phases for its completion, those are image acquisition, image registration and image blending.

The previous work done on panoramic view generation<sup>4</sup> is based on the fully automatic panoramic image stitching. Invariant features makes reliable matching of images under consideration. High quality results are obtained using multi-band blending<sup>3</sup> and automatic discovery of matching relationships between the images. Different algorithms have been used to generate a panorama but the prominent are Speeded up Robust Features<sup>2</sup> and Random Sample Consensus<sup>1</sup> algorithms. The SURF is an algorithm to describe and detect local features in images. Interesting points of an object denotes the features in an image and are generally used to identify the object in a particular image, and SURF is used to detect these features called the SURF features. RANSAC algorithm is used to detect the insignificant data. RANSAC algorithm is used to detect the odd points also known as outliers, RANSAC smooths/interprets the data with the higher percentage of errors like noise in the image.

In our work what we will be examining is given below:

---

\*Corresponding author. Tel.: +91-7813996949.

E-mail address: [iitianshubhankit@gmail.com](mailto:iitianshubhankit@gmail.com)

1. Can increase in the size of image improves the quality of blending?
2. If RQ 1 is true then what is the statistical claim?

## 2. Literature Review

Significantly we implement Local Beam Search (LBS) on the blob points obtained in SURF in order to find points which have high describing strength of detected feature.

In accordance with the D. Lowe's work<sup>2</sup>, SURF is used to find the blob points located at scale space maxima/minima of a difference of Gaussian function. Every feature location contains a characteristic scale, orientation & metric value attached to it. These blob points are in fact are all the discrete points on the surface of an image with some of the points restricted in the SURF due to the use of standard scaling. After getting the blob points by applying SURF, we will apply Local Beam Search (LBS) on the blob points to find those points which have high describing strength of detected feature. After applying LBS we will extract and match features and finally use random sample consensus<sup>1</sup> to estimate image transformation parameters and find a solution that has a best consensus with the data.

### 2.1 Related work

In Matthew's work<sup>4</sup> image stitching has been formulated as a multi-image matching problem and use of invariant local features to find matches between all the images, because of this their method is insensitive to the ordering, orientation, scale and illumination of the input images. Their paper has presented a novel system for fully automated panorama image stitching. Multi-band blending scheme ensures smooth transition between images despite illumination differences whilst preserving high frequency details.

In his work Scale Invariant Feature Transform and RANSAC have been successfully used to produce the panoramic image.

## 3. Motivation

The Matthew's paper<sup>4</sup>, on which this project's foundation is laid on, its ground work is fundamentally concentrating on the Scale Invariant Feature Transform (SIFT) and Random Sample Consensus algorithm (RANSAC). SIFT and RANSAC algorithm are already well established in the implementation of panorama generation in the real life.

The above research paper does not deal with the comparison of the final generated panorama image with the original non panoramic image in order of quality and effectiveness. The second limitation we encountered was that the final generated panoramic image differs in the size with the original non panoramic image. That's why we were motivated to come up with an experimental setup to study the quantitative outcome of the conventional SURF and RANSAC algorithm, to check the difference between the final generated panoramic image with the original non panoramic image. We will also implement the Local Beam Search (LBS) with the traditional SURF and RANSAC algorithm, because it is an optimized searching algorithm and is widely used in many applications because of its less memory requirements and compare our results of feature extraction time and Euclidean distance with the conventional SURF and RANSAC model.

## 4. Contribution

The traditional panoramic generation algorithm which uses speeded up robust features and random sample consensus is being used to generate panoramic image. As in accordance with our comparison table we have found some results which shows the variation between the original non panoramic image and finally generated panoramic image, in terms of Euclidean distance vector. So we will implement Local Beam Search because it is an optimized form of best first search and due to its less memory requirements to find the local maxima which is in this case the highest metric value point, to improve the final variation of Euclidean distance in the original non panoramic image and finally generated panoramic image and feature extraction and matching time of the two cropped images. We will also discuss the variation in the feature extraction time between two sets of input data, one having dimensions about  $400 \times 400$  and another having dimensions of  $800 \times 800$  in order to check whether increasing the dimensions of the images affect the modular time of feature extraction and matching.

## 5. Architecture

### 5.1 System design

In the system design of our proposed approach we have implemented our Local Beam Search in addition to the already well established SURF and RANSAC algorithms and obtain a panoramic image.

1. The first step of panoramic image generation using Local Beam Search is to divide an image firstly in 60:40 ratio and secondly in 40:60 ratio and taking the 60:60 portion of both the images as two input images.
2. Now the two cropped images are converted into grayscale format.
3. Now SURF (Speeded up robust features) algorithm is applied on the two cropped gray scale images obtained previously to detect the SURF features.
4. We will use Local Beam Search in order to extract those blob points (blob points are the regions in the image that differ in brightness and color compared to the surrounding regions.), which have high metric (value describing strength of detected feature) value.
5. We are dividing the whole image surface into small dynamic grids which are used to denote the different regions of the image space. After dividing the image into different dynamic grids we will apply local beam approach in every grid to detect the highest metric value point using the simple value comparison and finally get the filtered SURF points which are very less in number as compared to before.
6. After the RANSAC algorithm in which the images were blended<sup>3</sup> together and transformed either using projective or affine transformation. The final panoramic image is generated which is then compared with the original non panoramic image using Euclidean distance vector method.
7. We will also make a comparative study of variation in input sizes of images to check whether the increase in size of the input images makes our algorithm (LBS used with the conventional SURF and RANSAC) works better on the modular time taken for feature extraction and matching and also in reducing the variation in Euclidean distance between final panoramic image and nonpanoramic image.

The above depiction of our workflow is shown in the Fig. 1, which shows the sequence of steps that we have followed from taking the input images to calculating the Euclidean distance.

### 5.2 Algorithm

#### Automatic Panorama Stitching Using Local Beam Search

Step I. Take two images in RGB format by cropping the original non panoramic image.

Step II. Convert the images into grayscale format.

Step III. Apply SURF algorithm to detect SURF features.

Step IV. Dynamically divide the whole grid into several small grids.

Step V. For each small grid

Find the highest value of the describing strength of the detected feature, using the Local Beam Search Algorithm.

Step VI. Detect the features from the blob points received after the above approach.

Step VII. Now extract the features.

Step VIII. After extracting the features, match the features in the two grayscale images

Step IX. Apply RANSAC and image stitching.

Step X. Compare the finally generated panorama with the original non panoramic image using Euclidean Distance.

Output: Euclidean distance between the two images.

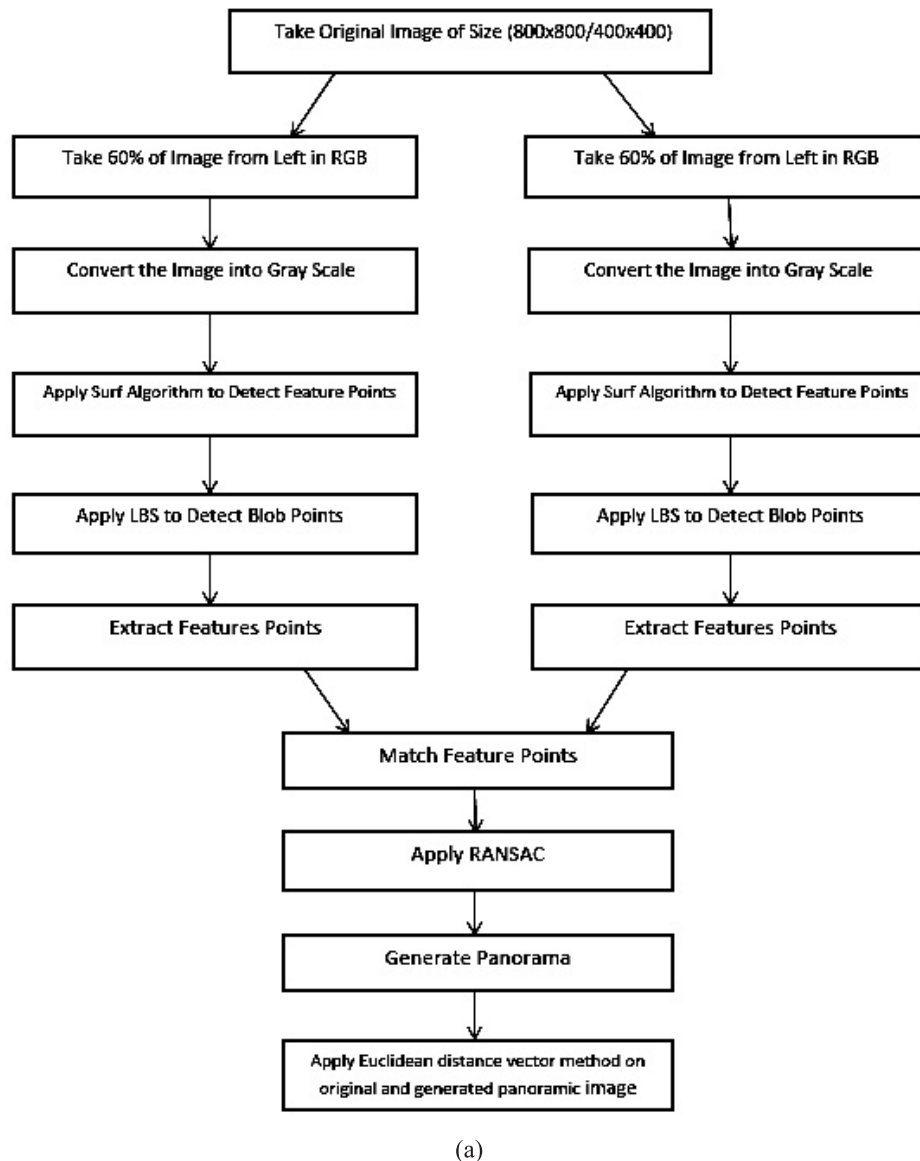


Fig. 1. System Design.

## 6. Experimental Setup and Result

Our experimental setup is made to analyse the panorama generated by the 60:60 part of original input images with the generated panoramic image. In our experimental setup as explained in the system design we have taken a non panoramic image of two dimensions and for both the images we have cropped them into 60:60 ratio and finally using SURF-LBS-RANSAC algorithm we have generated a panorama. A sample image structure of our workflow is shown in the Fig. 2.

After the implementation of our proposed approach on different set of images, we have tabulated some results based on a single set of images Fig. 2 as shown in Table 1.



Fig. 2. (a) Original non Panoramic Picture (Source: wallpaperscraft.com); (b) First Picture; (c) Second Picture; (d) Generated Panorama using SIFT-LBS-RANSAC.

Table 1. Results Obtained.

Dimension of Images and algorithm Used	Extract Feature Time (Total CPU Time)	Euclidean Distance (F)
800 × 800 Dimension, using SURF-LBS-RANSAC	0.104	8.434e-05
800 × 800 Dimension, using SURF-RANSAC	0.134	8.669e-05
400 × 400 Dimension, using SURF-LBS-RANSAC	0.031 0.050	0.0011 0.082

In Table 1 we have taken the original image Fig. 2(a) with two different dimension, one of around  $800 \times 800$  dimensions and another of  $400 \times 400$  dimension and then crop both of them into two different parts. After that both the approaches, the traditional SURF-RANSAC and our proposed approach was applied on the both set of images and we have found that the extract feature time of our proposed approach gives less time than the traditional one in both the dimension of images. Moreover the decrease in time between SURF-RANSAC and SURF-LBS-RANSAC is more

when taken higher dimension of images than lower dimension of images. As from the Table 1 the decrease in first two entries extract feature time is 0.030 which is around 30%, while in the last two entries it is 0.020 which is around 50%. Also the value of Euclidean distance is much lesser in higher dimension of images as compared to the images with the lower dimension.

## 7. Conclusions

We have analyzed conventional SURF-RANSAC algorithm and we have finally implemented an experimental setup to compare the original image with its generated panoramic image, depending on the SURF and RANSAC algorithm. This work has introduced the application of Local Beam Search (LBS) in accordance with SURF and RANSAC in order to obtain effective extracting and matching of SURF features. The experimental setup evaluates the generated panoramic image using LBS and without using LBS and compares with the original non panoramic image using Euclidean Distance Vector method. Our work has also introduced the comparison between the same image in two different dimensions regarding the time taken for extracting features and Euclidean distance between the conventional SURF-RANSAC algorithm and our SURF-LBS-RANSAC approach.

The improvised search SURF-LBS-RANSAC is proved to be better for the feature extraction modular time, where the results obtained have almost 30% reduction in the feature extraction time and also the Euclidean distance obtained is less than or somewhat comparable to the Euclidean distance obtained with the use of traditional SURF-RANSAC algorithm.

## Acknowledgements

The author would like to thank Sharmistha Majumder, Assistant Professor, Computer Science and Engineering Department, National Institute of Technology, Agartala, India and National Institute of Technology, Agartala computer laboratory for supporting and guiding us for the completion of this paper.

## References

- [1] Fischler and R. Bolles, Random Sample Consensus: A Paradigm for Model Fitting with Application to Image Analysis and Automated Cartography, In *Communications of the ACM*, pp. 381–395, (1981).
- [2] D. Lowe, Distinctive Image Features from Scale-Invariant Keypoints, In *International Journal of Computer Vision*, pp. 91–110, (2004).
- [3] M. Brown, R. Szeliski and S. Winder, Multi Imagematching using Multi-Scale Oriented Patches, In *IEEE* pp. 510–517, June (2005).
- [4] Matthew Brown and David G. Lowe, Automatic Panoramicimage Stitching using Invariant Features, In *International Journal of Computer Vision*, vol. 74, issue 1, pp. 59–73, August (2007).